REMOVAL OF GAUSSIAN NOISE FROM PHOTO-PLETHYSMOGRAHY (PPG) SIGNALS USING WAVELET TRANSFORMS

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Abstract- **Analysis of Bio-signals in the clinical side is gaining wide range of applications. These signals are degraded in their quality due the Motion artifacts which are alike Gaussian noise. A novel approach to remove the Gaussian noise from Photo-Plethysmographic (PPG) waveform using four different wavelets such as Haar, db2, db4 and near symmetric wavelet (symlet-8) is discussed in this paper. The hard and soft Thersholding techniques are used for this purpose. In this study four healthy subjects are analyzed. The Peak Signal to Noise Ratio (PSNR) measurements show the effectiveness of the different wavelets at two level of added Gaussian noise to the signal. The Hard Thersholding outperforms the Soft one with higher PSNR values.**

***Keywords* - Wavelet Denoising, PPG signals, Gaussian noise, Haar wavelet**

I. INTRODUCTION

Bio-signals are non-invasive procedures to quantify the healthiness of the organs based on their physiological maneuvers. For example the heart rate is naturally variable due to many physiological factors such as neural, hormonal, and mechanical forces [1]. Therefore, mechanical, electrical, and optical signals sensed from or generated by the heart will be inherently variable. From a signal processing point of view, this variation in heart rate is seen as a shift in frequency over time and is termed quasi-period [2]. Fast Fourier transform (FFT) analysis of pulse Oximeter signals have been shown to reduce the negative impact of motion artifact, alternate hemoglobin states, and low blood volume. However, FFT analysis has shown to perform poorly for quasi-periodic data sets [3].

In this paper a wavelet signal processing technique for PPG signals is explored as part of an on-going effort to build a unique technology. The need for such a system stems from the fact that reduces the multiple clinical examinations and earlier detection of peripheral vascular diseases before the patient is at serious risk. In developing this monitoring system, the need for a robust signal analysis algorithm has become apparent. The current sensor system contains three light sources (light emitting diodes of center wavelength 660nm, 810nm, and 940nm) that are independently modulated and electronically separated following detection. In the past these three signals have been analyzed using a standard FFT algorithm with some success [4], [7]. In an attempt to accommodate for the quasi-periodic signal obtained from this sensor, a wavelet analysis is explored in this paper.

II. METHODOLOGY

The block diagram for the analysis of PPG Waveforms with motion artifacts (Gaussian noise) is depicted in figure 1. PPG wave forms are obtained from four healthy subjects using Dolphin Medical 2100 Pulse Oximeter in the Medical Electronics laboratory at Thiagarajar College of Engineering –Madurai. The experimental investigations confirm to the principles outlined in the declaration of Helsinki published in Br.Med.JL.1964, ii, 177.The PPG waveforms are recorded for five minutes durations and sampled at 100 Hz through appropriate software coding. Then waveforms are added with Gaussian noise level of 1db and 2db levels to simulate a situation of motion artifacts. This combined signal is decomposed at various levels using four different wavelet transforms and the Thersholding effect of reconstructed PPG signal is analyzed.

The original and Gaussian noise added PPG waveforms of the healthy subject is shown below in fig 2. On visual inspection we can also identify the degrading effects of motion artifacts in the waveforms.

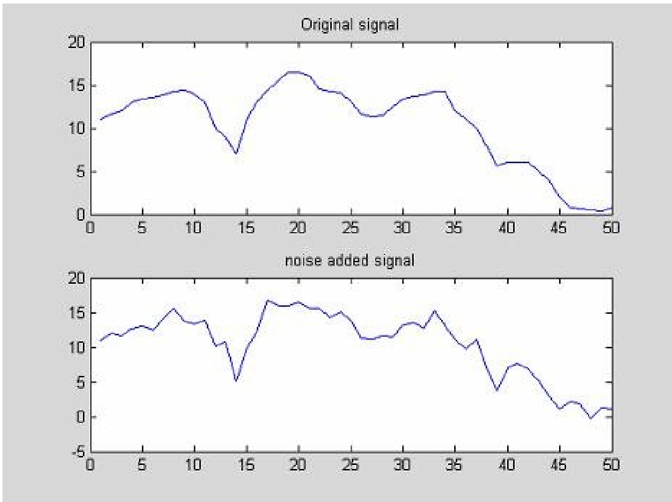

Fig. 2 Original and Gaussian noise added PPG Waveform from Healthy subject

Now the signal to noise ratio (SNR) of the signal is at the lower ebb [5]. There fore this is an SNR problem. Wavelet transforms are used to improve the signal's SNR value and to provide better reconstructed waveforms. The pertinent analysis of wavelet transforms are discussed in the following section of the paper.

III. WAVELET TRANSFORMS IN SIGNAL DECOMPOSITION

The wavelet transforms acts as a sort of mathematical microscope through which different parts of the signals are examined by adjusting the focus [8]. The wavelet transform (WT) of a function f (t) is an integral transform defined by [6],

$$wf(a,b) = \int_{-\infty}^{\infty} f(t)\psi^{*}_{a,b}(t)dt \qquad (1)$$

Where ψ^* (t) denotes the complex conjugate of the wavelet function ψ (t). The transform yields a time–scale representation similar to the time frequency representation of the short- time Fourier Transform (STFT). The set of the analyzing function the wavelet family is deduced from a mother wavelet ψ (t) by [10],

$$\psi^*_{a,b}(t) = \frac{1}{\sqrt{2}}\psi\left(\frac{t-b}{a}\right) \qquad (2)$$

Where a and b are the dilation (scale) and translation parameters respectively. The mother wavelet is a short oscillation with zero mean. The discrete wavelet transforms (DWT) results from discretized scale and translation parameters eg. $a=2^j$ and $b = n. 2^j$ where j & n are integer numbers. This choice of a and b leads to Dyadic DWT (DyDWT) [10].

$$wf(2^j, b) = \int_{-\infty}^{\infty} f(t) \bullet \psi^*_{2^j,b}(t)dt \qquad (3)$$

$$\psi_{2^j,b}(t) = \frac{1}{2^{j/2}}\psi\left(\frac{t-b}{2^j}\right) \qquad (4)$$

$$= \frac{1}{2^{j/2}}\psi\left(\frac{t}{2^j} - n\right) \qquad \text{And j, n } \in z$$

There have been several investigations into additive noise suppression in signals using wavelet transforms. Johnstone and Donoho's [10] principal work is on Thersholding the DWT of a signal and then reconstructing it. The method relies on the fact noise commonly manifests itself as smaller values, and wavelet transforms provides a scale based decomposition. Thus, most of the noise tends to be represented by wavelet coefficients at the finer scales. Discarding these coefficients would result in a natural filtering out of noise on the basis of scale [9]. Because the coefficients at such scales also tend to be the primary carriers of edge information, by setting the wavelet coefficients to zero if their values are below a threshold. These coefficients are mostly those corresponding to noise. The edge related coefficients, on the other hand, are usually above the threshold. In this study, at first the effect of simple Haar wavelet is undertaken. Haar wavelet function is defined as [10]

$$\psi(t) = \begin{cases} 1; 0 \le t < 1/2 \\ -1; \frac{1}{2} \le t < 1 \\ 0 : otherwise \end{cases} \qquad (5)$$

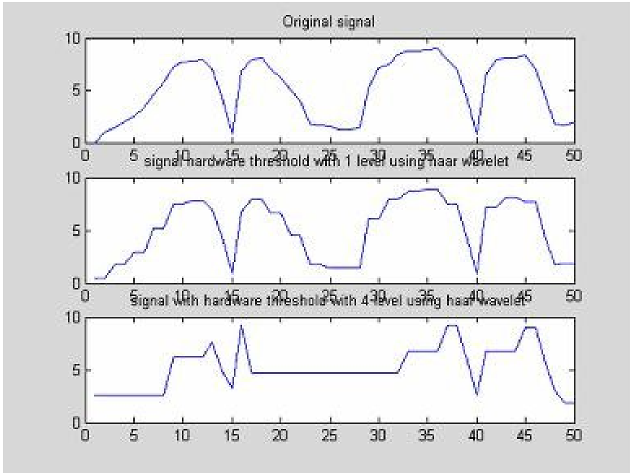

Fig 3. Analysis of Haar Wavelet in Decomposition of Noise free PPG Waveforms

The result of a four level decomposition of the noise free PPG signal with Haar wavelet is shown in fig 3. The outputs of the HPFs have high values at samples corresponding to the location of the edge. The leftward movement of peaks as we go from the level one HPF to the level four HPF is due to the factor of two down sampling at each stage. As is to be expected, the decomposition appears noisy. Let us thresholds for each HPF output using its standard deviation. The above figure 3 shows the result of reconstruction after hard Thersholding of the high pass outputs with the threshold at each level set to the output's standard deviation. However, we can notice the jaggedness o the reconstructed signals and this is due to the discontinuous nature of the Haar basis function. The higher the threshold, the lower the residual noise. However, noise removal is always accompanied by some degradation in the underlying signal, and increasing the threshold results in more of the signal component being zeroed out along with the noise.

If we go beyond the level 3 of the decomposition the symmetric nature of the PPG waveform is lost which was prevalent in the Haar wavelet decomposition. Therefore a tradeoff is necessary for the signal to preserve both the smoothness and symmetry. In this study, a near symmetric wavelet with 8 vanishing moments (symlet-8 wavelet) was used to characterize the PPG signal. The symlet-8 wavelet was chosen because of its near symmetric properties which are optimum for quasi-sinusoidal signals. This wavelet is able to minimize error without a large processing time making it ideal for clinical systems. The effect of sym8 wavelet is depicted in figure.4.

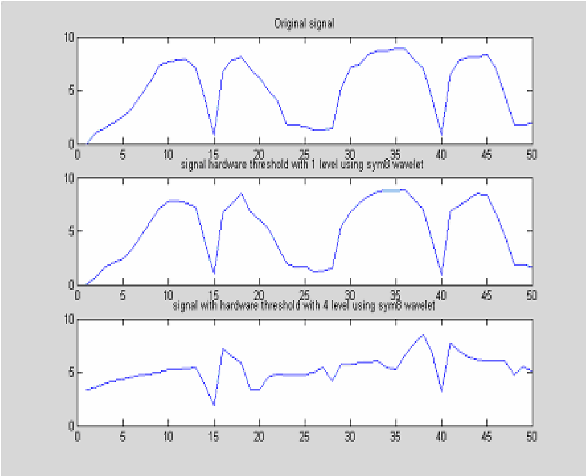

Fig 4. Analysis of Sym 8Wavelet in Decomposition of Noise free PPG Waveforms

And also it is noted that the smoothness and symmetric are well preserved in this wavelet decomposition method.

As we discussed already the motion artifacts are characterized by Gaussian noise and to remove this noise four different wavelet such as Haar, db2, db4 and sym8 are used. One such a type of Denoising the PPG waveforms using Haar wavelet using both hard Thersholding and soft Thersholding is shown in the figure.5

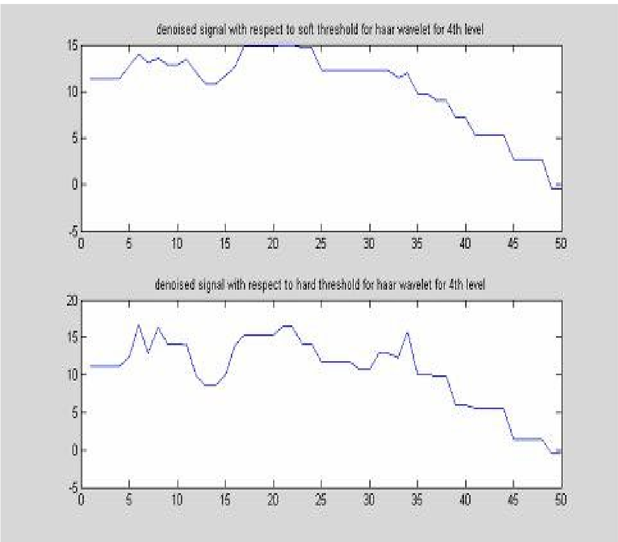

Fig 5. Denoising of PPG Waveforms using Haar wavelets

The four level Denoised and reconstructed signals outline the discontinuity nature of the Haar wavelet. The hard Thersholding characterize the signal up to the same level of noise free PPG signal analyzed as in the previous sections. The results of denoising the PPG signals using wavelet transforms are discussed in the following section.

IV. Results and Discussions

To select a better wavelet for Denoising and reconstruction of PPG waveforms we have to compare them on the basis of some metrics. One such a metric is known to be peak signal to noise ratio (PSNR) and is defined as [10]

$$PSNR(dB) = 10\log_{10}\frac{peak-absolute-value-of-signal}{mean-squared-noise} \qquad (6)$$

Higher the values of PSNR better the Denoising and reconstruction of the signal. Table I shows the comparison of PSNR values obtained through hard and soft Thersholding at noise power level of 1 Decibel and 2 Decibel for the smooth wavelets db2 and db4. The db2 wavelet with hard Thersholding at the level one for the Gaussian noise (motion artifact) of one db and 2db power is settled at higher value than its counter part db4 wavelets. Therefore we can select db2 wavelet to provide better smoothness in the motion noise driven PPG signal after Denoising. The PSNR values obtained through the Haar wavelets and sym8 wavelets are tabulated in the Table II. Table II shows that the Haar wavelet outperforms its counterpart sym8 wavelet with higher PSNR values of 32.1767 dB, which are almost 25 dB higher values than the syn8 wavelet. Therefore we can select Haar wavelet for better Denoising effect than smoothness of the reconstructed signal. The hard Thersholding provides better PSNR values than the soft Thersholding methods using all the four wavelet transforms. To meet the specific objects which are problem specific in nature we can select hard Thersholding for analyzing PPG waveforms with motion artifacts through Haar wavelet yields good results.

TABLE I
Comparison of PSNR for Db2 and Db4 wavelets

Type of wavelet	Levels	PSNR-noise power level 1 db		PSNR-noise power level 2 db	
		Soft threshold	Hard threshold	Soft threshold	Hard threshold
Db2	1	8.1153	**25.8008**	7.607	**25.1828**
	2	6.2487	**25.7530**	4.067	5.5305
	3	6.3548	8.1206	5.600	4.5903
	4	4.7116	6.5418	4.402	4.5941
	5	5.4911	6.0523	5.415	4.7782
	6	4.5865	6.0523	3.682	4.4412
Db4	1	5.4928	8.4363	5.253	5.2462
	2	6.8745	5.4149	4.812	7.1218
	3	4.4894	5.4149	5.234	7.1347
	4	4.9467	5.2180	4.921	5.6617
	5	4.5614	5.2042	3.588	5.3711
	6	4.4220	6.2251	4.179	5.3468

V. Conclusion

The objective of this paper is to analysis and identifies the better wavelet transforms for Denoising and characterizing the PPG waveforms is discussed. Four different wavelets are utilized for this purpose. Based on the smoothness and symmetric nature the wavelets are grouped into two groups and analyzed. To compare the performance of these wavelets PSNR value is used as a metric. Higher the PSNR values better the performing wavelet. In our case it is Haar wavelet is better suited for present condition. At present only four healthy subjects are analyzed and to obtain the global character this number has to be increased. Further research

will be carried out in analyzing PPG signal for peripheral vascular diseased patients through wavelet networks which is the combination of wavelet nodes with neural networks.

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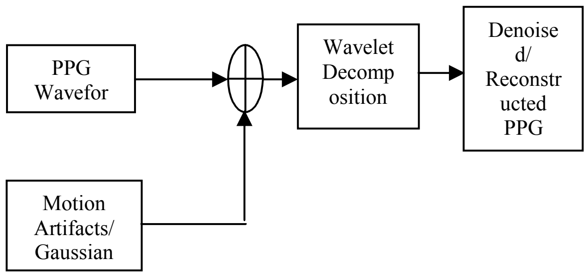

Fig 1.Block Diagram for Analysis of PPG Waveform with Motion Artifacts

TABLE II
Comparison of PSNR for HAAR and Sym8 wavelets

Type of wavelet	Levels	PSNR-noise power level 1 db		PSNR-noise power level 2 db	
		Soft threshold	Hard threshold	Soft threshold	Hard threshold
Haar	1	5.7901	**32.1767**	5.0887	**32.4388**
	2	4.3460	**31.7052**	5.3892	**32.2607**
	3	6.2177	**31.4783**	4.1572	**32.0667**
	4	4.5068	4.4130	4.0911	32.028
	5	3.8199	5.2010	4.1499	5.9236
	6	6.8506	5.9162	4.0531	5.9236
Sym 8	1	4.8692	5.5834	4.8376	5.2483
	2	4.4233	4.1576	4.1218	4.8448
	3	3.9560	5.4683	4.4687	6.4732
	4	5.3077	3.5511	4.1371	4.8557
	5	3.3054	2.9136	4.602	6.8693
	6	3.5383	4.3393	4.3705	6.0325